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ARTICLE

IoT-Driven Pollution Detection System for Indoor and Outdoor Environments

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ABSTRACT: The rise in noise and air pollution poses severe risks to human health and the environment. Industrial and vehicular emissions release harmful pollutants such as CO_2, SO_2, CO, CH_4, and noise, leading to significant environmental degradation. Monitoring and analyzing pollutant concentrations in real-time is crucial for mitigating these risks. However, existing systems often lack the capacity to monitor both indoor and outdoor environments effectively.This study presents a low-cost, IoT-based pollution detection system that integrates gas sensors (MQ-135 and MQ-4), a noise sensor (LM393), and a humidity sensor (DHT-22), all connected to a Node MCU (ESP8266) microcontroller. The system leverages cloud-based storage and real-time analytics to monitor harmful gas levels and sound pollution. Sensor data is processed using decision tree algorithms for classification, enabling threshold-based detection with environmental context. A Progressive Web Application (PWA) interface provides users with accessible, cross-platform visualizations.Experimental validation demonstrated the system's ability to detect pollutant concentration variations across both indoor and outdoor settings, with real-time alerts triggered when thresholds were exceeded. The collected data showed consistent classification of normal, warning, and critical states for methane, CO_2, temperature, humidity, and noise levels. These results confirm the system's reliability in dynamic environmental conditions.The proposed framework offers a scalable, energy-efficient, and user-friendly solution for pollution detection and public awareness. Future enhancements will focus on extending the sensor suite, improving machine learning accuracy, and integrating meteorological data for predictive pollution modeling.

KEYWORDS: Noise sensor; harmful air pollutants; PWA; gases and noise

1 Introduction

These days, the most serious threats to human health are those that come from pollution in the air and noise. Environmentally damaging air pollution is frequently caused by some factors, including the emission of harmful gases by industries, the emissions of vehicles, and the increased concentration of harmful and poisonous gases and particulate matter. The contaminated air can be atmospheric pollution either indoors or outside [1]. The air pollution that occurs outside is done so in an open environment, encompassing the entire atmosphere. Petroleum products that are used to control production lines, enterprises, and automobiles, as well as trash from agriculture and mining, are the primary contributors to the significant problem of air pollution in outdoor environments. There are a variety of pollutants that can be found in the air outside, including hydrocarbons, sulfur dioxides (SO_x), nitrogen oxides (NO_x), ozone (O_3), carbon monoxide (CO), and suspended particles and matter of numerous molecular sizes [2]. There are additional instances of indoor air pollution in places of employment, health facilities, school systems, digital libraries, gymnasiums, public transit, and other areas that are sources of indoor air contamination [3,4]. The severity of this issue is increasing daily, making it more essential than ever before to keep a close check on the levels of pollution and to take measures to manage the situation to ensure a prosperous society and better living. Fig. 1 shows the possible sources of indoor and outdoor air pollution. Data collectors used to travel far to gather and review data. The process often took a long time. However, Internet-connected sensors and micro-controllers make environmental parameter monitoring more flexible, precise, and comprehensive [5]. Although less effective than IoT, WSNs with sensors and Cloud are influential. A distant environment where things interact with the environment occurs when sensors and technology are combined. Poor outdoor and indoor air quality can cause sick building syndrome and other health issues. Natural ventilation reduces interior air pollution by regulating temperature [5,6]. Using natural ventilation, outdoor PM2.5 and traffic noise exceed 25 g/m^3 and 53 dB. WHO measured that building occupants are forbidden. Most researchers use cloud infrastructures and services with massive streaming data analytics. This prototype system is part of the latest IoT-based real-time detection and tracking for ambient AQI and noise levels [7,8].

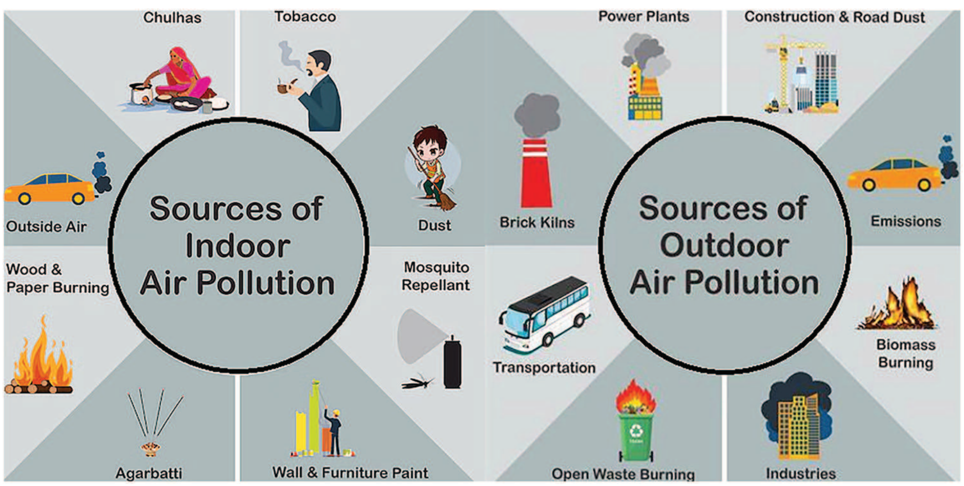

Figure 1: Possible sources of indoor and outdoor air pollution

In recent years, the proliferation of Internet of Things (IoT) technology has revolutionized various sectors, including smart cities, agriculture, and environmental monitoring. The ability to integrate IoT with real-time data collection and artificial intelligence (AI) has significantly enhanced decision-making capabilities, particularly in domains requiring continuous monitoring and automation.

Smart cities have emerged as one of the most promising applications of IoT, where interconnected sensors and devices facilitate efficient urban management. IoT-driven solutions have enabled authorities to respond proactively to environmental and infrastructural challenges, from traffic control to air quality monitoring. Federated Learning (FL) has been identified as a crucial approach in IoT applications, ensuring decentralized data processing without compromising privacy. This integration enables AI models to be trained locally on IoT devices, reducing the risk of data breaches while improving real-time analytics [9]. By applying FL-IoT frameworks, smart city applications can benefit from real-time monitoring of environmental pollutants, traffic congestion, and energy consumption, leading to enhanced sustainability and quality of life.

Recent research has emphasized the urgent need for effective indoor and outdoor air pollution monitoring due to the increasing impact of environmental pollutants on public health. IoT-based applications have emerged as cost-effective, reliable, and scalable solutions for this purpose. Alsamrai et al. [10] conducted a comprehensive systematic review of pollution monitoring systems and found that indoor air quality is particularly critical, as it directly affects the health and comfort of occupants. Their study revealed that over 39% of IoT-based systems focused on indoor environments, while outdoor monitoring accounted for only 20.79%, underscoring a research gap in balanced environmental coverage. Most systems utilized affordable sensors, ESP8266 microcontrollers, and cloud/web services for real-time monitoring, with Wi-Fi being the most common communication protocol.

Complementing this, Esfahani et al. [11] developed a battery-powered, low-cost IoT system designed for smart cities, capable of monitoring key parameters such as total VOCs, CO_2, PM2.5, PM10, temperature, humidity, and illuminance. The system interfaces with a smartphone application and provides actionable recommendations based on EPA standards to improve indoor air quality. These studies collectively highlight the growing trend of leveraging IoT for real-time air quality assessment and serve as a strong foundation for the development of our proposed framework that addresses pollution monitoring in both indoor and outdoor contexts.

Given the critical role of IoT in these applications, integrating IoT-based solutions into environmental pollution monitoring has become an essential research focus. The ability to track air quality parameters, detect hazardous pollutants, and predict environmental changes through AI models holds the potential to mitigate health risks and improve urban living conditions. Our proposed IoT-driven pollution detection system aligns with these advancements by providing a real-time, scalable, and accurate solution for monitoring air and noise pollution in both indoor and outdoor environments.

This article makes a significant contribution in the following ways: In the first place, we have developed the system to identify any potentially hazardous substances that may be present in the air by utilizing gas detection sensors (MQ-135 Gas Sensor, Winsen Electronics Technology Co., Ltd., Zhengzhou, China and MQ-4 Gas Sensor, Winsen Electronics Technology Co., Ltd., Zhengzhou, China) and noise sensors (LM393 Noise Sensor, Texas Instruments, Dallas, TX, USA) that are connected to the Node MCU (Node MCU (ESP8266), Espressif Systems, Shanghai, China) microcontroller. Second, the system is responsible for monitoring the level of pollution and noise, and once it has detected either of these factors, it transmits the data to a server that is located online. Third, when the number of pollutants reaches the limit, the microcontroller sends the notification to the Internet of Things gateways, which are responsible for transmitting data via the protocol HTTP. We have analyzed the data following the discovery of the system, which has resulted in the pollution of the environment in a variety of various ways [12,13]. The data from the analysis is displayed in the form of graph lines, allowing consumers to comprehend the influence that it has on activities through a web interface. Most of our efforts are focused on enhancing their degree of accuracy through analytical analysis, while simultaneously identifying pollutants that are present in the environment and drawing attention to them through the utilization of decision tree algorithms.

The main contributions of this study may be summarized as follows:

– Development of an IoT-Based Pollution Monitoring System: The proposed system integrates gas sensors (MQ-135 and MQ-4), a noise sensor (LM393), and a humidity sensor (DHT-22) connected to a Node MCU (ESP8266) Wi-Fi module for real-time environmental monitoring.
– Real-Time Data Collection and Cloud-Based Analysis: The system enables continuous air and noise pollution tracking, with data transmitted to a cloud-based platform for processing and visualization.
– Application of Decision Tree Algorithms for Enhanced Accuracy: The incorporation of machine learning techniques, particularly decision tree algorithms, improves pollutant classification and prediction accuracy.
– Progressive Web Application (PWA) for Data Visualization: A cross-platform PWA is developed, allowing users to access air quality data via mobile phones, tablets, and desktop devices.
– Comparison of Indoor and Outdoor Environmental Conditions: The study provides insights into how air and noise pollution levels vary across different environments, helping in identifying key sources of pollution.
– Scalability and Adaptability for Broader Applications: The system can be expanded to include additional sensors and AI models, making it suitable for smart city applications and environmental impact assessments.
– Automated Alert Mechanism for Pollution Threshold Breaches: When pollutant levels exceed predefined thresholds, the system triggers real-time notifications, allowing timely interventions.
– Potential for Future Integration with Weather Forecasting Models: The system lays the groundwork for integrating meteorological data to enhance predictive capabilities and mitigate pollution-related risks.

These contributions establish the proposed IoT-driven pollution monitoring framework as a scalable and effective solution for environmental assessment and public health protection.

This paper is structured as follows: Section 2 presents a detailed literature review, highlighting previous work and identifying research gaps. Section 3 explains the methodology, including data preprocessing, feature selection, and model development. Section 4 discusses the experimental results, comparing model performances based on key metrics. This section provides an in-depth discussion of the findings, and Section 5 concludes the study with key takeaways and future research directions.

2 Related Work

Numerous air quality monitoring systems have been developed and deployed for both indoor and outdoor environments. These systems leverage advancements in the Internet of Things (IoT) to enable real-time data collection and analysis, improving environmental monitoring and decision-making processes.

One of the primary benefits of IoT in air quality monitoring is its ability to facilitate seamless data transfer across networks without requiring human intervention [14]. IoT-based air quality monitoring systems integrate sensors such as DHT11 and MQ135, along with microcontrollers like Arduino Uno and Raspberry Pi, to detect harmful gases, including carbon monoxide (CO) and carbon dioxide (CO_2). These systems enable real-time monitoring of air quality through cloud-based platforms. Additionally, multi-sensor systems incorporating PMSA003, MICS-6814, MQ-131, and DHT-22 have been developed to expand pollutant detection capabilities, allowing for the monitoring of up to eleven different air contaminants. The ESP-WROOM-32 microcontroller, equipped with a Wi-Fi module, has been used to aggregate and transmit environmental data to cloud storage, further enhancing the predictive capabilities of artificial intelligence-driven models [15].

Real-time monitoring has evolved into intelligent systems, owing to advancements in IoT and sensor technology. Recent studies have demonstrated the efficacy of heterogeneous sensor networks combined with artificial intelligence methodologies, such as support vector machines, to detect carbon dioxide, nitrogen oxides, temperature, and humidity levels. The implementation of signal processing techniques plays a crucial role in ensuring accurate pollutant detection and improving data quality for subsequent environmental analysis. However, significant challenges remain in integrating smart sensors, AI-driven analytics, and wireless sensor networks (WSNs) in sustainable environmental management (SEM). The expansion of research in this area is anticipated to include broader environmental considerations, such as disaster response and noise pollution mitigation.

WSNs have played a crucial role in air quality monitoring, particularly in indoor settings. Systems integrating Arduino microcontrollers, CO and CO_2 sensors, temperature and humidity sensors, and Zigbee modules have been deployed for continuous indoor air quality assessment. These systems transmit collected data to Android applications and web portals, ensuring real-time data visualization. Typically, the architecture consists of a single gateway and multiple sensor nodes that communicate using Ethernet and web services. While such systems provide valuable insights into indoor environmental conditions, their sophisticated setup often lacks coordination and standardization [12,16]

The advent of IoT and cloud computing has led to the development of a wide array of real-time air quality monitoring solutions. Researchers have focused on integrating IoT-based platforms into monitoring frameworks to enable automated air quality assessments. While many existing studies have concentrated on refining IoT implementations for indoor air quality monitoring, future technologies are expected to further improve efficiency by integrating AI-driven predictive analytics and machine learning models.

A notable IoT-based framework employs MQ-2 gas sensors and actuators, such as Link wireless USB Adapters, L293D Motor Driver ICs, and ADS1115 ADCs, in conjunction with a Raspberry Pi 2 board. Python-based programming and various open-source libraries facilitate the data acquisition and processing pipeline [17]. The feasibility of this embedded platform has been demonstrated through its capability to evaluate and monitor air contaminants in real time. Additionally, such frameworks may be adapted for broader applications, including the Internet of Underwater Things (IoUT), for aquatic environmental monitoring.

Hybrid air quality monitoring systems have gained traction as a means of improving latency in data processing while enhancing real-time pollutant tracking. By combining IoT with edge computing, these systems reduce dependency on cloud infrastructure for initial data processing, ensuring faster responses and enabling more localized decision-making [18]. This approach minimizes the impact of network delays and enhances scalability, making it a viable solution for large-scale environmental monitoring deployments.

Recent work has also explored the use of Software-Defined Networking (SDN) to address end-to-end Quality-of-Service (QoS) challenges in heterogeneous IoT deployments. Ali et al. [19] proposed a multi-objective SDN-based framework designed to ensure reliable communication for low-power IoT devices, including delay-sensitive sensor applications in precision agriculture. Their two-layer SDN architecture includes an optimal additive weighting module (OAWM) and global controller statistics, which enable intelligent service mapping across multiple traffic classes. Such QoS-aware frameworks are directly applicable to scalable environmental monitoring systems where diverse sensor data must be reliably transmitted across distributed domains.

Recent advancements in AI-driven environmental monitoring have led to the integration of deep learning models such as CNNs and RNNs for air quality prediction. These models analyze historical and real-time sensor data to generate highly accurate forecasts, assisting policymakers and urban planners in mitigating pollution-related risks [20]. The adaptability of these models allows for continuous learning from environmental changes, improving long-term prediction reliability.

The deployment of IoT-driven air quality monitoring solutions has been instrumental in smart city initiatives, enhancing urban pollution management. By integrating real-time environmental data with traffic control and public health systems, smart cities can implement data-driven policies to improve air quality [21]. This includes adaptive traffic management, industrial emissions control, and responsive urban planning measures aimed at reducing pollution hotspots.

In parallel, blockchain technology has been explored as a means of securing and ensuring the integrity of environmental data collected through IoT sensors. Blockchain-based solutions provide a decentralized and tamper-proof record of air quality measurements, preventing data manipulation and enhancing trustworthiness [22]. This approach is particularly relevant in regulatory environments where data authenticity is critical for policy enforcement and compliance monitoring.

Citizen science and participatory sensing have emerged as valuable approaches for supplementing traditional air quality monitoring methods. Crowdsourced pollution data collected from mobile and wearable sensors enable broader geographic coverage and higher temporal resolution [23]. By empowering individuals to contribute real-time air quality measurements, these initiatives improve environmental awareness and foster community-driven advocacy for cleaner air policies.

A number of recent studies have proposed IoT-based frameworks for air and noise pollution monitoring, combining sensor networks with microcontrollers and cloud connectivity to enable real-time data analysis and public accessibility. Riteeka et al. [24] introduced a foundational system using basic gas sensors and Wi-Fi modules for ambient air monitoring, emphasizing cost-effectiveness and scalability. Sasane et al. [25] extended this work by integrating both air and sound pollution sensors, offering multi-pollutant detection in a unified IoT platform. Rakib et al. [26] presented a predictive air pollution monitoring system that leverages historical data and machine learning techniques for improved AQI estimation.

Saha [27] focused on responsive systems capable of triggering automated actions such as ventilation or alert mechanisms when pollution levels exceed safe thresholds. Dhingra et al. [28] proposed IoT-Mobair, a mobile pollution monitoring system for dynamic data collection in urban areas, while Yang [29] demonstrated the effectiveness of cloud-based dashboards for visualizing pollution patterns and supporting citizen engagement.

Advanced AI integration is evident in the work by Asha et al. [30], who used neural networks for environmental toxicology and real-time air quality classification, and by Almalawi et al. [31], who proposed a hybrid AI technique for pollution prognosis and anomaly detection in large-scale deployments. Popescu et al. [7] emphasized the role of IoT-AI synergies in policy-oriented environmental management and public health monitoring.

These studies reflect the evolution of IoT-based pollution systems from static sensing toward intelligent, connected ecosystems that support prediction, automation, and stakeholder engagement. A comparative summary of core features is presented in Table 1.

Table 1: Comparative analysis

Feature	Description	References
Real-time monitoring	Continuous data collection and instant access to pollution levels via cloud-connected systems	[26,28,29]
Multi-pollutant detection	Simultaneous measurement of gases, particulates, noise, humidity, and temperature	[25–27]
Cloud-based analytics	Cloud platforms enable visualization, trend analysis, and remote access for stakeholders	[24,26,29]
Alerts and automation	Systems send warnings or trigger controls (e.g., fans, actuators) when thresholds are exceeded	[27,30]
Low-cost and scalable deployment	Use of affordable sensors and microcontrollers for city-wide or modular applications	[24,25,28]
Machine learning prediction	Use of AI/ML models (e.g., ANN, hybrid models) to forecast AQI and detect anomalies	[30,31]
Public health and awareness	Mobile apps and dashboards empower users with real-time pollution data	[7,27]

Despite significant advancements in IoT-based environmental monitoring, several challenges remain unaddressed, justifying the need for the proposed system. The following research gaps highlight the limitations of existing approaches and establish the relevance of this study:

- Limited Integration of Real-Time Monitoring and AI-Based Analysis: Existing air quality monitoring systems often lack real-time processing capabilities or rely on conventional data collection methods without integrating AI-driven predictive analytics. The proposed system incorporates decision tree algorithms to enhance pollutant detection and classification.
- Inconsistent Indoor and Outdoor Pollution Assessments: Many existing studies focus on either indoor or outdoor air quality, without providing a comparative analysis of pollution levels across different environments. This research bridges this gap by offering a comprehensive evaluation of both settings.
- Lack of User-Centric and Accessible Data Visualization: While various IoT-driven monitoring frameworks exist, most fail to provide an intuitive, cross-platform interface for end-users. The implementation of a Progressive Web Application (PWA) ensures accessibility and ease of use across multiple devices.
- Insufficient Automation in Pollution Alert Mechanisms: Conventional monitoring solutions often lack proactive notification systems to alert users when pollutant levels exceed safe thresholds. The proposed system addresses this by integrating automated alert mechanisms for timely interventions.
- Scalability and Adaptability Constraints: Most current systems lack modularity, making them difficult to extend for broader applications such as smart city deployments or weather-based pollution forecasting. This study proposes a scalable architecture capable of integrating additional sensors and AI models for future enhancements.

– Data Storage and Processing Limitations: Many air quality monitoring solutions depend on local storage or inefficient data transmission techniques, resulting in delayed analytics. By leveraging cloud-based data storage and analysis, this research ensures efficient real-time monitoring with improved computational efficiency.

By addressing these gaps, the proposed system advances the field of IoT-based environmental monitoring, providing a more comprehensive, adaptive, and efficient solution for tracking and mitigating air and noise pollution.

3 Materials and Methods

The development of this IoT-based system is crucial for human health as it aims to monitor harmful pollutants and noise levels in real-time. The system has been designed using various sensors to ensure that concentrations of dangerous pollutants like Carbon Dioxide (CO_2), Methane (CH_4), Nitrogen Dioxide (NO_2), Carbon Monoxide (CO), and Ammonia (NH4) can be measured accurately. The use of these sensors also allows for controlling noise levels in the environment, further enhancing the overall monitoring capabilities of the system.

The development of the Smart Air Analysis system will follow the Rapid Application Development (RAD) model to ensure efficient and timely progress. The objectives outlined for the system will be met through real-time monitoring and determination of temperature, humidity, and concentration of noise and pollutant gases present in the surrounding environment [32,33]. By gathering data from sensor networks, the system will analyze and compare the data to identify trends and patterns. With the use of IoT technology, the system can propose intelligent and multi-functional solutions to reduce air pollution, leading to improved environmental quality and human health.

Overall, this IoT-based system has the potential to revolutionize the way air pollution is monitored and controlled. With its ability to provide real-time data, it can assist in identifying pollution sources and help authorities take necessary steps to reduce pollution levels. The multi-functional capabilities of the system, coupled with the use of IoT technology, make it an essential tool for addressing the pressing issue of air pollution.

The smart-air environment, which is an IoT-based air quality monitoring platform, was established on the cloud web server [34]. To collect data for analyzing air quality, the sensing devices used included a laser, a CO sensor, a CO_2 sensor, an LM393 sensor, and a temperature and humidity sensor, as depicted in Fig. 2. The following components were utilized in the system:

– Microcontroller: Arduino (Node MCU ESP8266 (WI-FI) module)
– Wireless Sensors: Temperature and humidity sensor (DHT-22), Carbon dioxide sensor (MQ-135), Methane gas sensor (MQ-4), Noise sensor (LM393)
– Cloud Computing-Based Web Server: PHP/MySQL, RESTFUL APIs, Bootstrap (HTML/CSS/JavaScript)

The smart-air environment utilized these components to collect and analyze air quality data, making it a comprehensive and effective IoT-based system for monitoring and reducing air pollution.

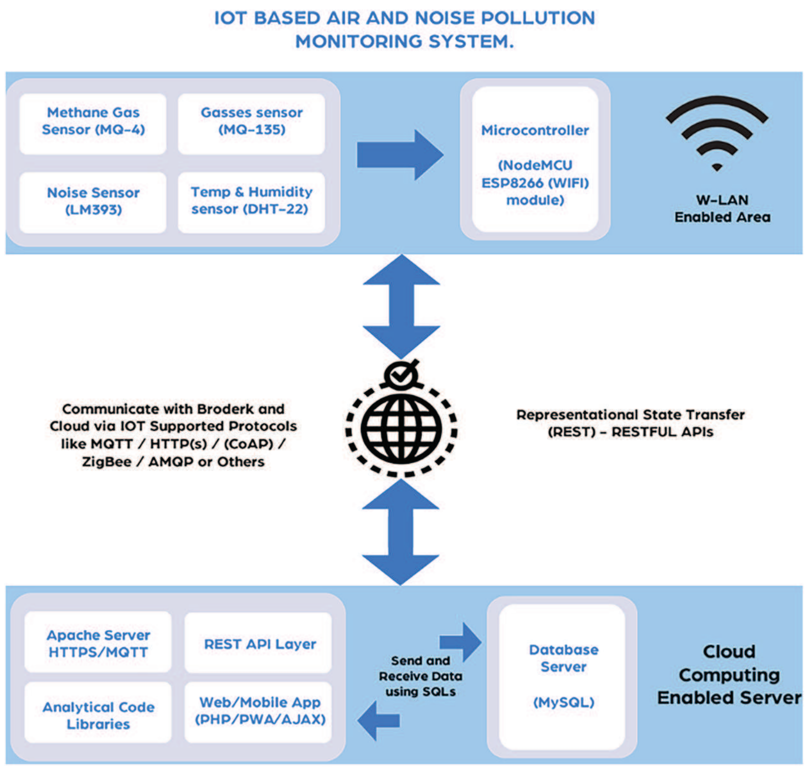

Figure 2: An IoT-based air and noise pollution analysis system architecture

3.1 Sensor Specifications

Pollutants such as ammonia (NH3), sulphur (S), benzene (C_6H_6), carbon dioxide (CO), and smoke, together with other toxic gases, have the potential to cause damage to various habitats, including those found inside and outside. In addition to being able to detect these gases, the MQ-135 Gas Sensor possesses both a digital and an analog output pin that is brought to a high state once the concentration of these gases in the air reaches a predetermined threshold limit. A potentiometer that can be adjusted and is situated on the back of the sensor can be rotated to improve its sensitivity, which in turn provides the best results for determining gas concentrations [35,36].

The MQ-4 gas sensor is employed for detecting methane gas concentration in both indoor and outdoor environments, particularly in critical situations. This sensor provides dual signal outputs, namely digital and analog values. To optimize sensitivity for gas concentration detection, a potentiometer located on the sensor's backside can be adjusted [37]. The DHT22 sensor utilizes a temperature and humidity sensor, along with a specialized NTC for temperature detection, and an 8-bit microprocessor for serial data output to gather temperature and humidity values [38]. It can be interfaced with the Node MCU ESP8266 to provide real-time data. In our project, this sensor is used to monitor humidity and temperature levels to assess air quality.

The MQ-135 and MQ-4 gas sensors used in this study were calibrated using basic zero-point and span adjustment techniques. The sensors were exposed to clean air and known gas concentrations to establish a working range for analog outputs. However, no multi-point calibration against certified gas analyzers was conducted, which is a limitation of this work. Due to environmental variations and the low-cost nature of these sensors, output values can fluctuate with temperature, humidity, and sensor aging. Signal averaging over short windows (3–5 readings) was employed to reduce transient noise.

Noise is a common issue in outdoor environments. The LM393 is a comparator IC designed to detect electrical pulses. It includes a condenser microphone for measuring sound levels from the source. The LM393 is mounted on a small board with a microphone (50 Hz–10 kHz) and circuit connections to convert sound waves into electrical signals. The captured signal is routed to the OUT pin, and a 10 K potentiometer is used to fine-tune the sensitivity for alerts. The detail specification of sensor type is described in Table 2.

Table 2: The detailed specifications of used sensors

Sensors type	Gases sensed	Specifications
MQ-135	NH_3, CO_2, Benzene, Sulphur & Smoke.	Temperature: 20°C ± 2°C; Humidity: 65%–5%; Related Humidity: >95% RH; Sensing resistance: 30–200 kΩ; Detection range: for NH_3 (10–300 ppm), for C_6H_6 (10–1000 ppm) Operating voltage: 0~5 V
MQ-4	Methane gas, Natural gas, LPG & CNG.	Humidity: 65% + 5%; Related Humidity (RH) > 95% RH; Temperature: 20°C ± 2°C. Sensing Resistance: 20–60 kΩ. Detection Range: 300 to 10,000 ppm. Operating Voltage: 3~5 V
DHT-22	Humidity & Temperature	Resolution: 16-bit; Repeatability: ±1%RH, Temperature: ± 0.2°C; Accuracy: in humidity ±2% RH, Max: ±5% RH; in temperature: <±0.5°C; Response time 2 s; Power Supply: 3.3~6 V
LM393	Noise & Sound	Microphone Sensitivity: 52 to 48 dB, Operating voltage: 3.3 to 5.5 V, PCB size: 3.4 cm * 1.6 cm; Dimensions: 32 mm × 17 mm; Frequency range: 100–10,000 dB

3.2 Methods and Implementation

Fig. 3 shows the present design of the Internet of Things device, which incorporates a microcontroller (ESP Wi-Fi Module) and multiple sensors (DHT-22, MQ-135, MQ-4, and LM393). The Node MCU ESP8266 microcontroller gathers and distributes data from these sensors. Monitoring and detecting dangerous air pollutants like CO_2, O_2, SO_2, and CO is the main function of the gadget. It will sound an alarm when their levels exceed the allowed limits.

The micro-controller forwards this data to IoT gateways, which utilize the HTTP protocol to transfer the information to a cloud server via REST APIs over a Wi-Fi connection [39]. The gathered data is then stored in a cloud database and analyzed using a progressive web application (PWA). Analytical insights are derived from SQL queries, producing graphs, tables, and charts that illustrate the daily and monthly trends in rising gas concentrations over time.

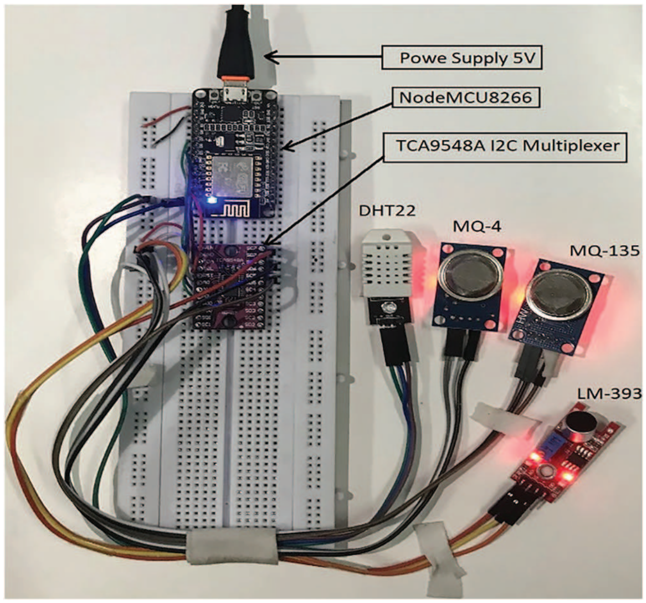

Figure 3: IoT Air and Noise quality sensor hardware

The data and gas concentrations that were acquired from the device are displayed in the final report that is generated by the entire system. Users are provided with valuable information regarding the air pollutants that are present in their environment by means of this Internet of Things system, which provides a solution that is both comprehensive and efficient for monitoring indoor air quality. The sophisticated analytics and data visualization capabilities that are utilized by this system make it an invaluable resource for researchers and policymakers in the process of detecting and addressing environmental issues that are associated with air pollution.

4 Results and Discussions

The experimental setup involved real-time data collection using the proposed IoT-based pollution monitoring system. As shown in Fig. 4, the system recorded sensor data at a sampling rate of one reading per minute, capturing 25 consecutive readings over a 25-min duration. Each record included synchronized values from gas sensors (MQ-135 and MQ-4), noise sensor (LM393), and the temperature/humidity sensor (DHT-22). The data was transmitted via Wi-Fi and stored on a cloud-based platform for further analysis using the Progressive Web Application (PWA). This experimental snapshot illustrates the real-time responsiveness and integration of the system. Future deployments will extend the observation period and enable detailed performance benchmarking across broader timeframes and environmental conditions.

Our team has developed an Air Quality Analysis System that is capable of detecting gas levels in both indoor and outdoor environments. The system is equipped with sensors that collect data in real-time, which is then transmitted to the cloud via an HTTP protocol. The progressive web application allows users to view the concentration levels of pollutants in the air, providing valuable insights into the air quality.

To detect gas leakage, such as natural gas and LPG, we have incorporated the MQ-4 sensor into our system. Fig. 4 represents the concentration of gas leakage in a fixed area, whether indoor or outdoor. The progressive web application (PWA) displays the detected values stored in the database that are fetched from the cloud. Our system employs algorithms and pseudo-codes to ensure that all the readings remain under a certain threshold value. Furthermore, our system is capable of calculating the Air Quality Index (AQI) using the MQ-135 sensor. The MQ-135 sensor can detect concentrations of carbon monoxide ranging from 20 to 2000 ppm. Fig. 5 displays the graph that uses the analog resistance to give an output, which is represented through the graph line. The AQI reading is displayed through the progressive web application, allowing users to understand the air quality in their environment.

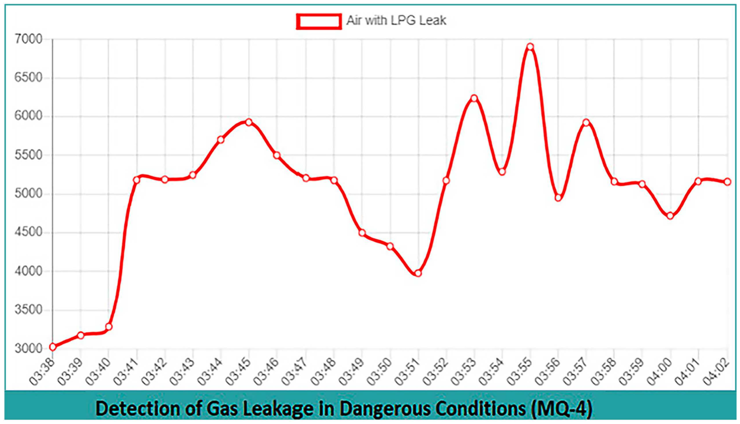

Figure 4: Detection of LPG in conditions

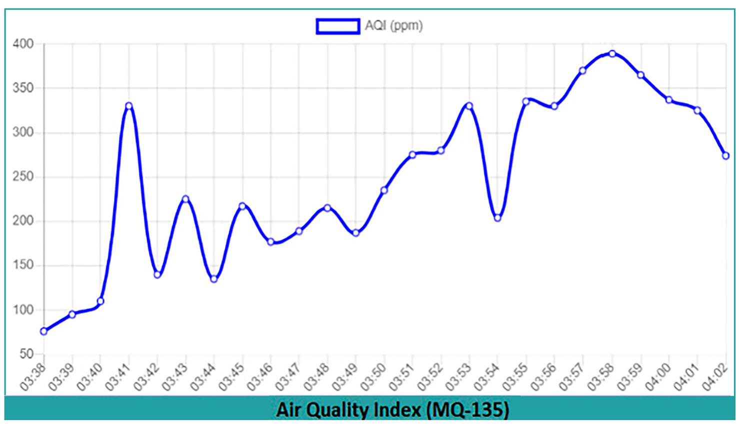

Figure 5: Air quality index calculated in the graph line

Overall, our Air Quality Analysis System provides a comprehensive solution for monitoring air quality in both indoor and outdoor environments. The system's progressive web application offers users an easy-to-use interface to visualize the data collected by the sensors. The integration of algorithms and pseudo-codes ensures that the readings remain within the permissible range, providing users with accurate and reliable data.

Fig. 6 presents the time series of ambient temperature and relative humidity measured with the DHT22 sensor. Across both indoor and outdoor settings, a clear inverse relationship is observed: as temperature decreases, relative humidity increases (and *vice versa*). The sensor's digital output enables synchronized, high-resolution logging of both variables.

Fig. 7 shows the outdoor noise profile. The LM393-based sound module converts the microphone signal into voltage levels that are sampled by the microcontroller and transmitted to the cloud via HTTP. In the time-series plot, increases in measured sound level (dB) appear as upward excursions/spikes of the trace.

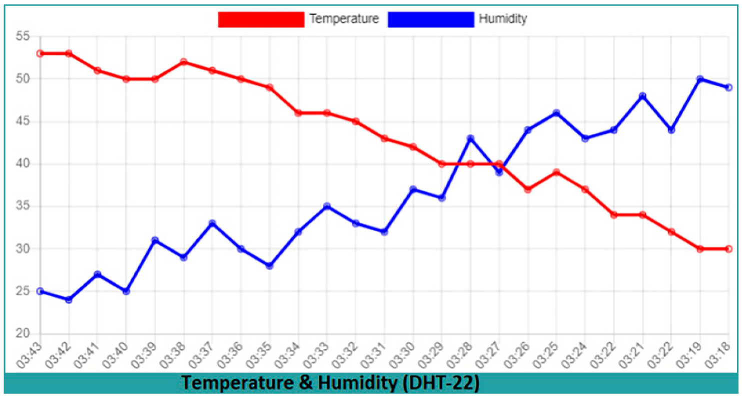

Figure 6: Temperature and humidity calculated

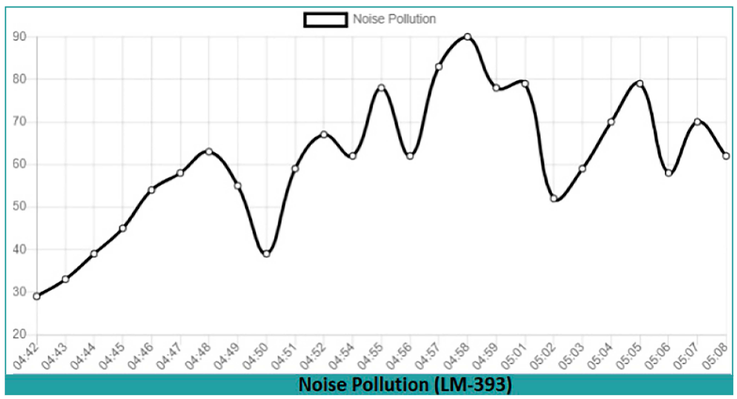

Figure 7: Noise pollution calculated in graph line

4.1 Outdoor Simulation Results

During the outdoor trials, the recorded values remained within the user-specified ranges. Temperature and relative humidity again exhibited the expected inverse trend, with warmer periods corresponding to lower relative humidity and cooler periods to higher relative humidity. Environmental disturbances—such as rain, wind gusts, or storms—may transiently alter these measurements. For example, precipitation and wind can both modify the local temperature–humidity profile and elevate the apparent noise level, introducing short-lived variability in the graphs.

Fig. 8 displays the digital temperature and humidity readings collected by the DHT-22 sensor. Our analysis has revealed that the temperature in the environment tends to decrease, and the humidity increases in outdoor settings. This information can help understand the climate and environmental conditions, especially for those who suffer from allergies or respiratory problems. In addition to this, Fig. 9 represents the noise pollution levels detected in the outdoor environment by the LM393 sensor. This sensor can detect the range of sound in decibels (dB) through the microphone. When the sensor detects sound, it processes the output signal voltages, which are then sent to the microcontroller and transmitted to the cloud via HTTP. The increment in decibel signals is displayed as a graph line, which can be used to monitor and analyze noise pollution in the environment.

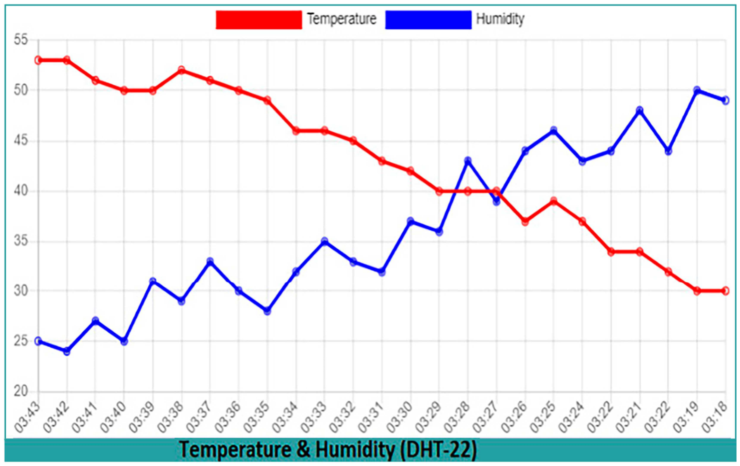

Figure 8: Temperature and humidity calculated

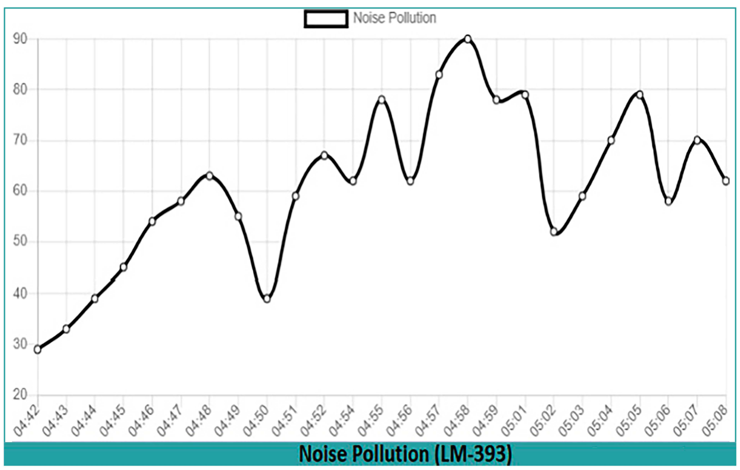

Figure 9: Noise pollution calculated in the graph line

Fig. 10 provides a comparison of the results obtained from the various sensors used in our Air Quality Analysis System. The analysis of the sensors is displayed through the Progressive Web Application (PWA), which is accessible through web-based and android applications and desktops. The readings obtained from the sensors can be used to observe the behavior of gas concentrations in the environment, whether they are increasing or decreasing. The information obtained from the sensors can be used to take appropriate measures to improve the air quality in our surroundings.

Overall, the Air Quality Analysis System offers a comprehensive solution for monitoring and analyzing various environmental factors, including gas concentrations, temperature, humidity, and noise pollution. The Progressive Web Application provides users with an easy-to-use interface to view and analyze the data collected by the sensors. The system's capabilities can be used to improve air quality and promote a healthy and safe environment for everyone.

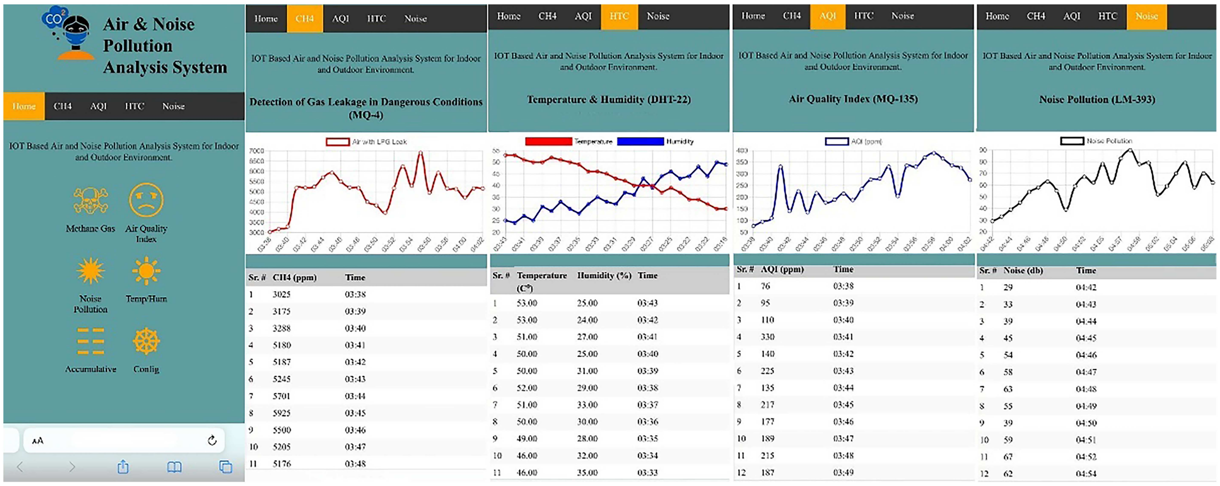

Figure 10: Android application interfaces

4.2 Indoor Simulation Results

The results of the experiment conducted in an indoor environment were different from those obtained in an outdoor setting due to the absence of external factors. Fig. 11 shows the temperature and humidity levels recorded by the DHT-22 sensor in the indoor environment. It was observed that the temperature and humidity levels were higher indoors. Fig. 12 represents the noise pollution detected in the indoor environment using the LM393 sensor, which measures the sound level in decibels (dB). The microphone sensor placed inside the model detects the sound, and the output signal voltages are processed by the sensor, which is then sent to the microcontroller and transmitted to the cloud via HTTP. The graph line shows the incremental changes in the decibel levels recorded in the indoor environment.

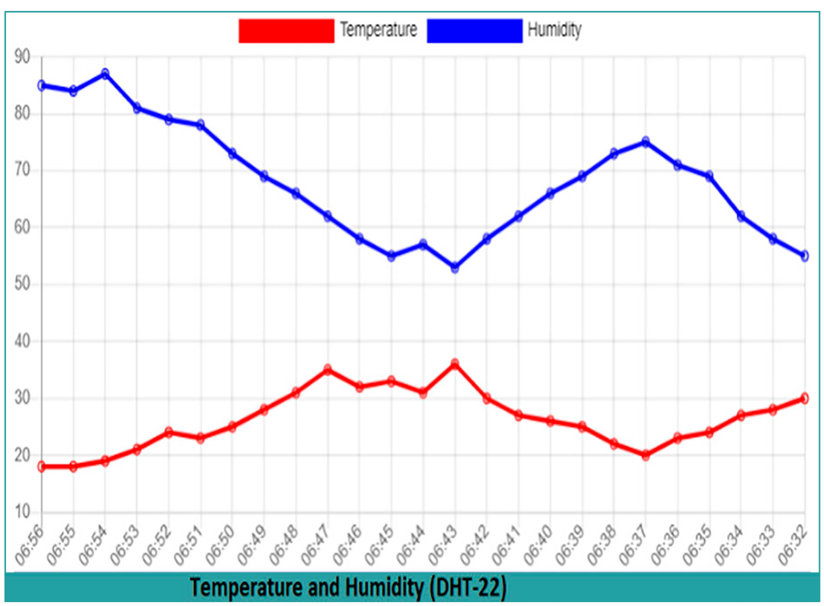

Figure 11: Temperature, humanity

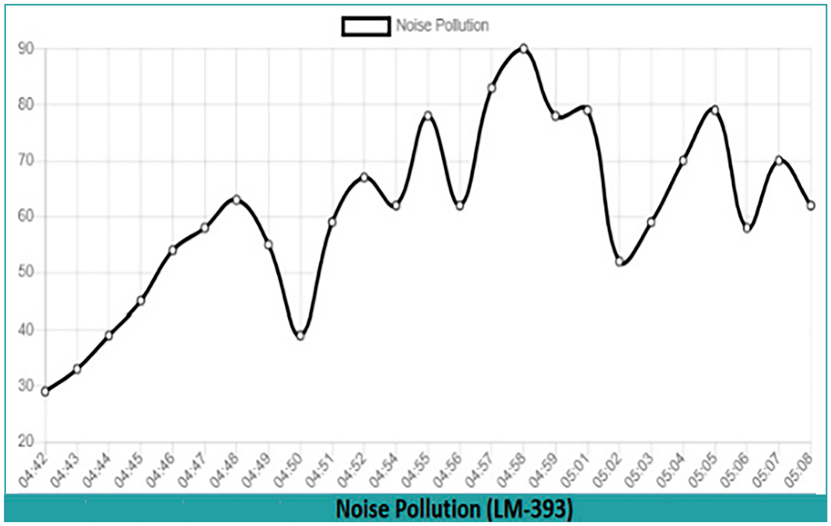

Figure 12: Noise pollution calculation

Comparing the results obtained from the indoor and outdoor environments, Fig. 13 highlights the differences in gas concentrations and noise pollution levels. The behavior or analysis of the sensors in both environments is shown through the Progressive Web Application (PWA), which is compatible with web-based, android applications, and desktops. Through the PWA, users can view and analyze the data collected by the sensors and observe the changes in the environment over time.

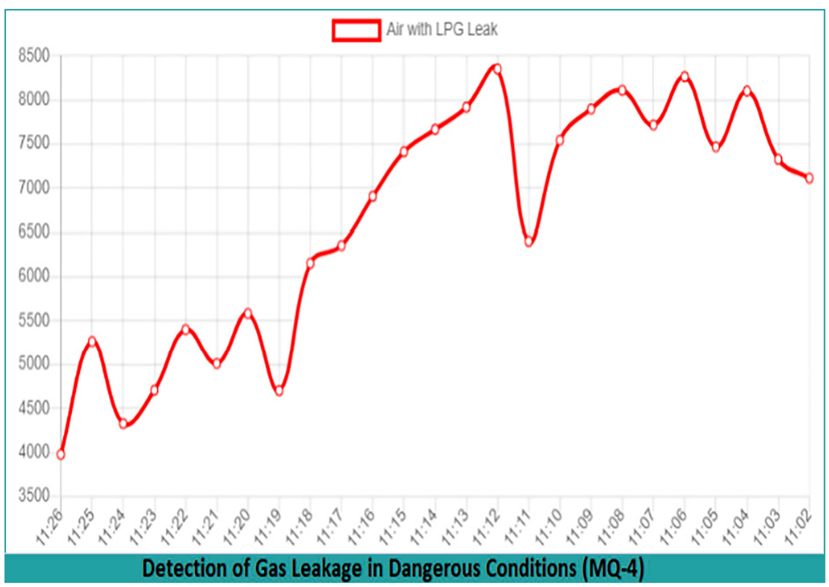

Figure 13: Detection of LPG by MQ-4

In Fig. 14, the Air Quality Index (AQI) calculated through the MQ-135 sensor is depicted. This sensor detects the concentration levels of carbon monoxide and dioxides present in the indoor environment, ranging between 20 and 2000 ppm. The analogue resistance signals generated by the MQ-135 sensor are used to provide an output signal that is displayed on the graph line. The graph line shows the changes in concentration levels of these pollutants over time, which can help users understand the air quality in the indoor environment and take necessary actions to improve it. The data collected by the sensors and displayed through the PWA can be used to track changes in air quality and identify potential sources of pollution.

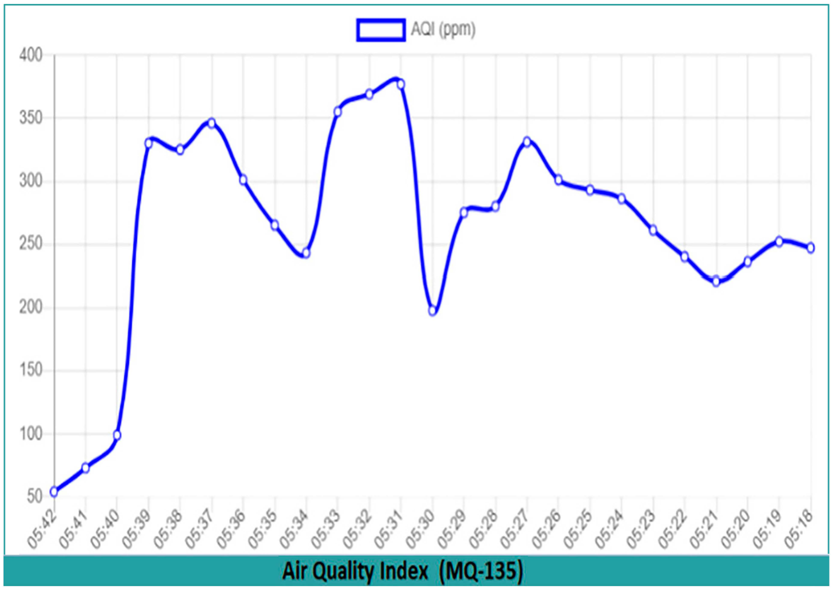

Figure 14: Air quality index calculated by MQ-35

4.3 Accumulative Results

Over a few minutes, the graph displays the readings that were received from the cloud. In each of these sensors, accumulative graph lines are displayed in the manner indicated in. Because they cannot be higher than one hundred degrees Celsius, the lines that represent temperature and humidity are straight. As can be seen in Fig. 15, specific individuals are displaying slopes promptly that correspond to their movement and concentration profiles.

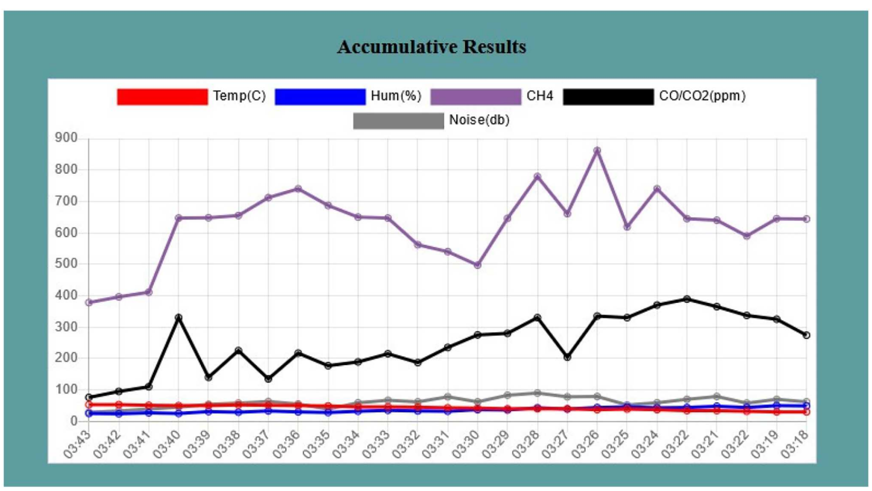

Figure 15: Accumulative results graph lines showing the behavior of gases over time

4.4 Implementation of Decision Tree Algorithms in Outdoors

We selected decision tree algorithms for pollutant classification due to their suitability for deployment in real-time, resource-constrained IoT environments. Compared to complex machine learning models such as support vector machines (SVMs) or neural networks, decision trees offer faster inference, require minimal memory, and provide easily interpretable rule-based outputs. These characteristics make them ideal for embedded microcontroller applications, where lightweight and transparent decision logic is crucial. Future work may explore the comparative performance of ensemble methods like Random Forest or Gradient Boosting to further improve prediction robustness.

The decision tree implementation in our system is instrumental in predicting values that exceed predefined limits, offering a proactive approach to identifying potential issues. Fig. 16 illustrates the outcomes of our system, highlighting readings that surpass these limits. This capability allows for early detection and intervention, ensuring timely responses to maintain optimal environmental conditions. The grayscale signals denote appropriate levels of configurations, while orange readings imply moderate levels. On the other hand, dangerous gas and noise concentrations are indicated by red values. By comparing the data with the minimum and maximum threshold values, these determinations are established. By classifying environmental situations in this way, we can respond quickly whenever dangerous amounts are detected.

The machine learning server runs on the AQNAS (Air Quality and Noise Pollution Analysis System), which mainly supports real-time predictions and the data collected from the gases and noise sensors. The web page server has been updated with the predicted results. The projections were made in two modes: firstly, a real-time prediction was made for a specific time, and secondly, a prediction was created for particular minimum and maximum values of these configurations, which are collected through the system. A prediction is made by using a color scheme that highlights good, moderate, and hazardous gases in collected data using the MySQL database server, and the results are analyzed using Algorithms 1 and 2.

Sr. #	CH4 (ppm)	Time
1	3025	03:38
2	3175	03:39
3	3288	03:40
4	5180	03:41
5	5187	03:42
6	5245	03:43
7	5701	03:44
8	5925	03:45
9	5500	03:46
10	5205	03:47
11	5176	03:48
12	4500	03:49
13	4325	03:50
14	3978	03:51
15	5173	03:52
16	6235	03:53
17	5288	03:54
18	6902	03:55
19	4952	03:56
20	5921	03:57
21	5161	03:58
22	5126	03:59
23	4720	04:00

Sr. #	AQI (ppm)	Time
1	76	03:38
2	95	03:39
3	110	03:40
4	330	03:41
5	140	03:42
6	225	03:43
7	135	03:44
8	217	03:45
9	177	03:46
10	189	03:47
11	215	03:48
12	187	03:49
13	235	03:50
14	275	03:51
15	280	03:52
16	330	03:53
17	204	03:54
18	335	03:55
19	330	03:56
20	370	03:57
21	389	03:58
22	365	03:59
23	337	04:00

Figure 16: Decisions in readings and reporting for MQ4 and MQ135 sensor

Algorithm 1: Decisions in readings and reporting for MQ-4 sensor readings

```
Begin
Threshold = (th)
Set th_low   = 100
Set th_high   = 180
Set mq135_sensor_readings =input:(select readings from mysql  database)
For each cur_value  in mq135_sensor_readings
Switch (cur_value)
Case (cur__value   < th_low
Print "normal state"
Break
Case (cur_value   > th_low  and cur_value   < th_high)
Print "warning state"
BREAK
Case (cur__value   > th_high)
Print "critical state"
Break
End switch
End foreach
End
```

Algorithm 2: Decisions in readings and reporting for MQ-135 sensor readings

```
Begin
Threshold = (th)
Set th_low   = 100
Set th_high   = 180
Set mq135_sensor_readings =input:(select readings from mysql  database)
For each cur_value  in mq135_sensor_readings
Switch (cur_value)
Case (cur__value   < th_low
Print "normal state"
Break
Case (cur_value   > th_low  and cur_value   < th_high)
Print "warning state"
Break
Case (cur__value   > th_high)
Print "critical state"
Break
End switch
End for each
End
```

It is important to note that IoT sensors such as MQ-135 and MQ-4 are susceptible to drift and variability due to environmental interference, aging, and voltage fluctuations. Although basic calibration was performed and signal averaging applied, this system may still be prone to false positives or false alarms under unstable conditions. No confidence intervals or error margins were computed in this prototype stage. Future versions will incorporate adaptive filtering, long-term sensor drift compensation, and cross-validation against certified air quality instruments.

Regarding the decision thresholds (e.g., low = 100, high = 180), these were selected empirically based on sensor datasheet guidance and field behavior observed during pilot testing. These are not formally tied to WHO or EPA standards and will be updated in future work to align with regulated AQI index frameworks.

Fig. 17 shows MQ4 sensor decisions and reporting. As mentioned in the technique section, decision tree algorithms or PHP code implement regular, moderate, and extreme dangerous gas concentrations. MQ135 sensor determinations and reporting reveal gas AQI levels on time. Decision tree algorithms implement regular, mild, and perilous gas concentrations, as shown in the highlighted measurements.

Sr. #	Temperature (C^{0})	Humidity (%)	Time
1	53.00	25.00	03:43
2	53.00	24.00	03:42
3	51.00	27.00	03:41
4	50.00	25.00	03:40
5	50.00	31.00	03:39
6	52.00	29.00	03:38
7	51.00	33.00	03:37
8	50.00	30.00	03:36
9	49.00	28.00	03:35
10	46.00	32.00	03:34
11	46.00	35.00	03:33
12	45.00	33.00	03:32
13	43.00	32.00	03:31
14	42.00	37.00	03:30
15	40.00	36.00	03:29
16	40.00	43.00	03:28
17	40.00	39.00	03:27
18	37.00	44.00	03:26
19	39.00	46.00	03:25
20	37.00	43.00	03:24
21	34.00	44.00	03:22
22	34.00	48.00	03:21
23	32.00	44.00	03:22

Sr. #	Noise (db)	Time
1	29	04:42
2	33	04:43
3	39	04:44
4	45	04:45
5	54	04:46
6	58	04:47
7	63	04:48
8	55	04:49
9	39	04:50
10	59	04:51
11	67	04:52
12	62	04:54
13	78	04:55
14	62	04:56
15	83	04:57
16	90	04:58
17	78	04:59
18	79	05:01
19	52	05:02
20	59	05:03
21	70	05:04
22	79	05:05
23	58	05:06

Figure 17: Decisions in readings and reporting for DHT-22 and LM393 sensor

Fig. 17 represents the decisions and reporting done through the DHT22 temperature and humidity sensor. Highlighted readings show the normal, moderate, and extreme hazardous levels of increasing temperature and decreasing humidity here. The implementation of the excessive level of values after the threshold is detected by using decision tree algorithms or code as listed above in the methodology section of this paper.

The LM393 noise sensor provides decisions and reports the noise level (ppm) over time. The highlighted readings show the normal, moderate, and harmful levels of noise increasing in both indoor and outdoor surroundings. That is implemented by using decision tree algorithms as mentioned in the above section. Algorithm 3 shows the decisions in readings and reporting for LM393 sensor readings, while Algorithm 4 shows the decisions in readings and reporting for DHT-22 sensor readings.

Algorithm 3: Decisions in readings and reporting for LM393 sensor readings

```
Begin
Threshold = th
Set th_low = 30
Set th_high = 60
Set lm939_sensor_readings = input:(select readings from mysql database)
Foreach cur_value in lm939 sensor readings
Switch (cur_value)
Case (cur__value < th_low)
Print "normal state"
Break
Case (cur_value > th_low and cur_value < th_high)
Print "warning state"
Break
Case (cur__value > th_high)
Print "critical state"
Break
End switch
End foreach
End
```

Algorithm 4: Decisions in readings and reporting for DHT-22 sensor readings

```
Begin
Threshold = th
Set temp_th_low = 30
Set temp_th_high = 60
Set hum_th_low = 30
Set hum_th_high = 60
Set dht22_sensor_readings = input:(select readings from mysql database)
For each cur_value in dht22 sensor readings
        -decisions on temp readings
    Switch (cur_value)
    Case (cur_value > hum_th_high)
    Print "humidity: normal state"
        break
    Case (cur_value > hum_th_low and cur_value < hum_th_high)
    Print "humidity: warning state"
        break
    Case (cur__value < hum_th_low)
    Print "humidity: critical state"
        break
    End switch
    Switch (cur_value)
```

(Continued)

Algorithm 4 (continued)

```
        Case (cur_value  < temp_th_high)
        Print "temperature: normal state"
          break
    Case (cur_value  > temp_th_low  and cur_value  < temp_th_high)
    Print "temperature: warning state"
    Break
    Case (cur__value  < temp_th_low)
          Print "temperature: critical state"
          Break
          End switch
  End forearch
  End
```

4.5 Implementation of Decision Tree Algorithms in Indoors

In the indoor environment, the system was tested, and the readings were found to have changed due to no interruptions. The results were more accurate and precise compared to the outdoor environment. Our system utilizes a decision tree implementation to predict values that are outside the limit. Normal, moderate, and hazardous gas and noise concentration levels are identified through gray, yellow, and red readings, respectively, based on the minimum and maximum values from the threshold established in a pre-designed web interface.

Fig. 17 depicts the decisions and reporting done by the MQ4 sensor. Decision tree algorithms highlight the regular, moderate, and extremely hazardous levels of gas concentrations, resulting in precise and controlled values from the sensor, making the environment less harmful than the outdoors. Fig. 18 represents the decisions and reporting of the MQ135 sensor, which shows the Air Quality Index (AQI) level of gases promptly. The highlighted readings indicate the normal, moderate, and harmful gas concentration levels, which are more precise and less toxic than those outdoors.

While the current implementation focuses on real-time prediction using decision tree logic within a lightweight embedded system, we acknowledge the absence of formal statistical metrics (e.g., accuracy, precision, recall, and F1-score) as a limitation. This is primarily due to the deployment-oriented nature of the prototype, where the focus was on integration and functionality rather than offline performance benchmarking. Future work will incorporate quantitative evaluation frameworks to assess model performance more rigorously using labeled datasets.

We conducted an indoor test using the same sensor models with specified configurations, namely the DHT22 and LM393. We obtained results that differed slightly from the outdoor readings due to the absence of external factors. However, the indoor readings still provide a reliable indication of the air quality within that setting. Our system employs a decision tree algorithm to forecast whether the readings exceed a certain threshold. We have categorized the readings into three levels: grey for standard, yellow for moderate levels that are still acceptable, and red for hazardous levels of gas and noise concentrations. These decisions are based on the minimum and maximum values specified in the system's web interface. These results were considered by using Algorithms 5 and 6.

Sr. #	CH4 (ppm)	Time
1	3977	11:26
2	5266	11:25
3	4327	11:24
4	4705	11:23
5	5401	11:22
6	5009	11:21
7	5584	11:20
8	4701	11:19
9	6153	11:18
10	6355	11:17
11	6904	11:16
12	7409	11:15
13	7663	11:14
14	7915	11:13
15	8348	11:12
16	6402	11:11
17	7541	11:10
18	7896	11:09
19	8106	11:08
20	7714	11:07
21	8261	11:06
22	7466	11:05
23	8098	11:04
24	7324	11:03
25	7111	11:02

(a)Decisions in readings and reporting for MQ4 sensor

Sr. #	AQI (ppm)	Time
1	54	05:42
2	73	05:41
3	99	05:40
4	330	05:39
5	325	05:38
6	346	05:37
7	301	05:36
8	265	05:35
9	243	05:34
10	355	05:33
11	369	05:32
12	377	05:31
13	198	05:30
14	275	05:29
15	280	05:28
16	331	05:27
17	301	05:26
18	293	05:25
19	286	05:24
20	261	05:23
21	240	05:22
22	221	05:21
23	236	05:20
24	252	05:19
25	247	05:18

(b)Decisions in readings and reporting for MQ135 sensor readings.

Figure 18: Decisions and reporting through the MQ4 and MQ135 sensor

Algorithm 5: Decisions in readings and reporting for MQ-4 sensor readings

```
Begin
Threshold = (th)
Set th_low   = 3500
Set th_high   = 5500
Set mq4_sensor_readings =input:(select readings from mysql  database)
For each cur_value  in mq4_sensor_readings
If cur__value   < th_low  then
Print "normal state"
Else if cur_value   > th_low  and cur_value   < th_high  then
Print "warning"
Else if cur_value  $   > $  th  high then
Print "critical"
End if
End foreach
End
```

Algorithm 6: Decisions in readings and reporting for mq-135 sensor readings

1. Begin
2. Threshold = (th)
3. Set th_low = 100
4. Set th_high = 180
5. Set mq135_sensor_readings = input:(select readings from mysql database)
6. For each cur_value in mq135_sensor_readings
7. If cur_value < th_low then
8. Print "normal state"
9. Else if cur_value > th_low and cur_value < th_high then
10. Print "warning"
11. Else if cur_value > th_high then
12. Print "critical"
13. End if
14. End foreach
15. End

Fig. 19 shows the decision-making process and reporting based on readings obtained from the DHT22 sensor, which indicates accurate measurements for temperature and humidity levels. During indoor testing, the system successfully detected moderate levels of less harmful pollutants, and the readings displayed by the DHT22 sensor were consistent with expected outcomes. On the other hand, Fig. 19 displays the decisions and reporting performed using the LM393 noise sensor, indicating that the noise levels in the indoor environment are generally low. However, during instances when the noise levels increase due to human activity in the vicinity, the red highlighted areas indicate when the noise levels exceed the pre-defined threshold limit.

Sr. #	Temperature (C°)	Humidity (%)	Time
1	18.00	85.00	06:56
2	18.00	84.00	06:55
3	19.00	87.00	06:54
4	21.00	81.00	06:53
5	24.00	79.00	06:52
6	23.00	78.00	06:51
7	25.00	73.00	06:50
8	28.00	69.00	06:49
9	31.00	66.00	06:48
10	35.00	62.00	06:47
11	32.00	58.00	06:46
12	33.00	55.00	06:45
13	31.00	57.00	06:44
14	36.00	53.00	06:43
15	30.00	58.00	06:42
16	27.00	62.00	06:41
17	26.00	66.00	06:40
18	25.00	69.00	06:39
19	22.00	73.00	06:38
20	20.00	75.00	06:37
21	23.00	71.00	06:36
22	24.00	69.00	06:35
23	27.00	62.00	06:34
24	28.00	58.00	06:33
25	30.00	55.00	06:32

Sr. #	Noise (db)	Time
1	35	08:12
2	38	08:13
3	62	08:14
4	41	08:15
5	48	08:16
6	54	08:17
7	82	08:18
8	80	08:19
9	62	08:20
10	89	08:21
11	55	08:22
12	51	08:23
13	45	08:24
14	42	08:25
15	83	08:26
16	90	08:27
17	78	08:28
18	74	08:29
19	59	08:30
20	61	08:31
21	75	08:32
22	79	08:33
23	58	08:34
24	65	08:35
25	47	08:36

Figure 19: Decisions and reporting by DHT22 and LM393sensor

Recent work by Bakirci [40] demonstrates that pollutant distributions around buildings can vary significantly due to building geometry and local outdoor conditions, challenging the common assumption of spatial homogeneity. Drone-based measurements revealed pollutant accumulation patterns that strongly influence indoor air quality, underscoring the need for spatially adaptive sensing strategies. While our system employs fixed-location sensors for simplicity, future work will explore multi-point or mobile sensing to better capture these spatial effects.

5 Conclusions

The increasing levels of pollution due to industrial and vehicular emissions have resulted in hazardous pollutants such as CO_2, SO_2, CO, CH_4, and noise exceeding safe thresholds. Addressing this environmental concern requires efficient detection and analysis mechanisms to safeguard human health and the ecosystem.

In response, this study has developed an IoT-based pollution detection system that provides an online portal and mobile application to monitor air quality levels in real-time.

By leveraging Decision Tree algorithms, the system accurately analyzes pollutant concentrations, considering the minimum and maximum threshold values of each sensor. This analytical approach enhances the system's ability to categorize harmful gases and noise pollution, enabling rapid decision-making for both indoor and outdoor environments. Through its real-time monitoring capabilities and user-friendly data visualization, the system offers a practical solution for individuals, policymakers, and researchers to take proactive measures in minimizing pollution exposure and improving environmental quality.

Future Directions

Despite the effectiveness of the proposed system, several challenges remain, necessitating further research and development. One of the primary concerns is the need for a scalable IoT infrastructure that can support multiple sensor nodes distributed over large geographical areas. Additionally, sensor calibration and lifespan limitations present challenges in ensuring long-term reliability and accuracy.

To address these issues, future research can focus on:

- Expanding Sensor Capabilities: Incorporating additional sensors such as MQ6, MQ7, MQ9, PM2.5, PM10, and MHZ-14 to improve pollutant detection coverage and enhance data collection accuracy.
- Enhancing Environmental Computing with IoT: Implementing smart filtering mechanisms to screen fine dust particles, automate ventilation systems, and regulate air conditioning based on real-time pollution levels.
- Machine Learning-Based Predictions: Developing advanced machine learning models to predict air quality trends based on historical and real-time data, enabling proactive pollution mitigation strategies.
- Integration with Weather Forecasting: Incorporating meteorological data to refine pollution predictions and optimize environmental monitoring.
- User-Centric Enhancements: Expanding the online portal and mobile application with real-time air quality updates, personalized health recommendations, and a feature for users to report localized pollution concerns.

By addressing these future research directions, the proposed system can evolve into a more robust, intelligent, and adaptive framework, ultimately contributing to a safer and healthier environment for all.

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Author Contributions: Fatima Khan and Tariq Shahzad perform the Original Writing Part, Software, and Methodology; Sunawar Khan and Tehseen Mazhar perform the Rewriting, investigation, design Methodology, and Conceptualization; Tariq Ali, Tariq Shahzad, Tehseen Mazhar and Amna Khan perform related work part and manage results and discussions; Habib Hamam, Tehseen Mazhar and Amna Khan perform related work part and manage results and discussion; Fatima Khan, Sunawar Khan and Tariq Shahzad perform Rewriting, design Methodology, and

Visualization; Tehseen Mazhar, Muhammad Adnan Khan and Habib Hamam performs Rewriting, design Methodology, and Visualization. All authors reviewed the results and approved the final version of the manuscript.

Availability of Data and Materials: The data that support the findings of this study are available upon reasonable request from the corresponding authors.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

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